PREDICTION METHODS AND DATA FUSION FOR PROGNOSTICS OF PRIMARY AND SECONDARY BATTERIES

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Abstract: A method to accurately assess the state-of-charge (SOC), state-of-health (SOH), and state-of-life (SOL) of electrochemical energy sources provides significant benefit to operational systems. The model-based effort described here is focused on predictive diagnostics for primary and secondary batteries. It can also be applied to other electrochemical energy sources, such as fuel cells. This method is based on accurate modeling of the transport mechanisms within the battery and requires carefully developed electrochemical and thermal models. New features are developed from these models and are used in conjunction with several traditional measured parameters to assess the condition of the battery. Data fusion of feature vectors is used to develop inferences about the state of the system. The resulting output and any usage information available about the battery is then evaluated using hybrid automated reasoning schemes consisting of neural network and decision theoretic methods. The focus of this paper is on model identification and data fusion of the monitored and virtual sensor data. The methodology and analysis presented is applicable to mechanical systems where multiple sensor types are used for diagnostic assessment.

Key Words: Automated reasoning; condition-based maintenance; data fusion; electrochemical impedance; model-based diagnostics; predictive diagnostic techniques; state-of-charge

Introduction: Batteries are an integral part of many machines and are critical backup systems for many power and computer networks. Failure of a battery could lead to loss of operation, reduced capability, and downtime. An efficient way to monitor a battery's performance and assessment of its condition could drastically increase the reliability of these systems. The present condition of a battery is described nominally with the state-of-charge (SOC), which is defined as the ratio of the remaining capacity and the initial or rated capacity. Thus, the service history of a cell and its nominal capacity impact the assessment of SOC. Secondary batteries are observed to have a capacity that deteriorates over the service life of the cells. The term state-of-health (SOH) is used to describe the physical condition of the battery, ranging from external behavior such as loss of rated capacity, to internal behavior such as severe corrosion. The remaining life of the battery (i.e. how many cycles remain, usable charge, etc.) is termed the state-of-life (SOL), the prognostic metric. In this paper, a model-based effort is presented for predictive diagnostics of primary and secondary batteries. The flow of the model-based predictive diagnostics processing is shown in Figure 1. There are five distinct stages of the

processing: 1) measurement of signals related to diagnostics; 2) extraction of key features (such as model parameters); 3) charge, health, and life prediction; 4) decision processes that combine the predictions with knowledge and history; and 5) output of user information for display or coordination with other systems. The specific objectives of the model-based approach described here are determination of the SOC, SOH, and SOL.

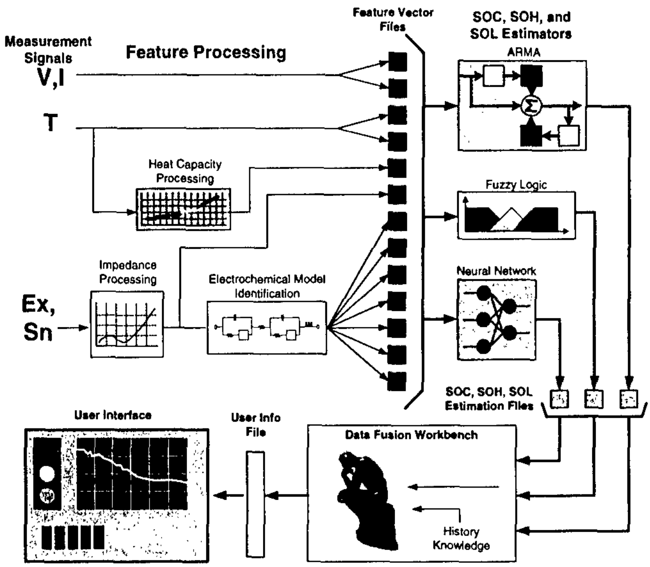

Figure 1. Flow diagram of developed predictive diagnostics processing

Model-based Approach: The general approach to model development is to formulate robustly parameterized governing equations for energy conservation and relevant electrochemical phenomena and transport processes. Lumped parameter formulation in lieu of a spatially distributed formulation offers greater applicability to the broad variety of cell chemistries and battery designs. That is, explicit geometry and configuration input are not required. The parameters and sources of the various transport, state, and conservation equations are coupled to ensure consistency with experimental observations and facilitate system classification. The model parameterization is formulated to incorporate significant aging mechanisms and pathological behavior in order to provide fault diagnostic capability. The ability to forecast future battery performance is developed by tuning system parameters through history-matching trials.

Data Fusion Techniques: A core challenge is to develop the appropriate signal processing, sensor-level data fusion, and automated reasoning to support battery diagnostics, charge control, and ultimately, prognosis of remaining cycles. Multi-sensor data fusion techniques that combine data from actual and virtual sensors provide the potential to improve detection performance and reduce the number of false alarms [1].

Automated Reasoning: The hybrid automated reasoning modules developed previously at the Pennsylvania State University Applied Research Laboratory (ARL) integrate a variety of predictive diagnostic techniques, such as neural networks, fuzzy logic, and auto-regressive moving average (ARMA) models, via decision-level data fusion[2], [3]. The outputs of these techniques are three estimates of the battery state and optimal charge control based on electrochemical and thermal data and available usage information. They are combined using hybrid automated reasoning modules, consisting of neural network and decision theoretic methods, to provide a single estimate of the battery's state. This output can be obtained as a linguistic indication or as numerical indication and is coupled with a measure of confidence. This type of tool is beneficial because it utilizes key information from multiple estimations for robustness and presents the results of the fusion assessment, rather than a mere data stream.

Measurement and Data Collection: The first step to developing model-based diagnostics is to establish the necessary and available observables (i.e., what can be measured and its sufficiency). Changes in the electrode surface, diffusion layer, and solution are not directly observable without disassembling the battery cell. Other variables, such as potential, current, and temperature, are observable and can be used to indirectly determine the performance of physical processes. This is the rationale for choosing a model-based approach. Under these constraints, the following types of measurements were selected for battery diagnostics: terminal and cell voltages, load currents, surface and internal temperatures, electrolyte pH, and electrical impedances. To ensure maximum coverage of operating modes for testing developed algorithms, test stand data were collected under the following conditions:

1. No load, fully charged
2. Once every minute while discharging
3. No load, 100% discharged
4. Once every minute while charging

An ongoing experimental test schedule is being conducted under an Office of Naval Research (ONR) sponsored battery project, where lead-acid, nickel-cadmium, lithium, and alkaline batteries are being run to failure. During a test, battery impedance data is collected along with cell and terminal voltages, load current, and temperatures at various internal and external locations on the battery. To date, over 200 data sets have been collected across the different chemistries and sizes of batteries.

Electrochemical Impedance Model Identification: Direct measurements of battery or cell condition have traditionally been very difficult for practical systems such as automotive or aviation batteries. There are, however, a variety of indirect measurement techniques that rely on the cell's response to a precise manipulation of the load [4], [5], [6]. One of the most robust and widely used methods in laboratory practice is AC Voltammetry. This technique can provide information on the electrochemical dynamics of the battery through a non-invasive interrogation of the cell. By applying a small amplitude excitation to the cell and measuring the response, the internal impedance of the cell can determine. Figure 2 represents the measured impedance of a nickel-cadmium battery that has been partially discharged.

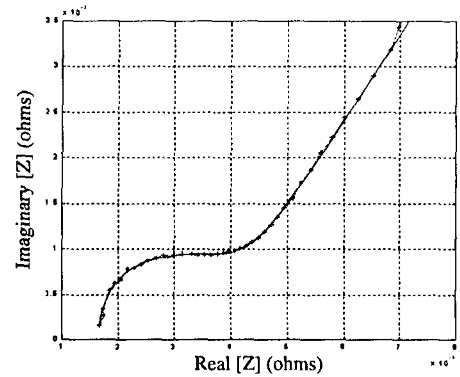

Figure 2. Impedance of 4.3 Amp-hour nickel-cadmium battery, partially discharged and fit to impedance model

Internal impedance measurements can further be used to retrieve information about the electrochemical processes that occur within the battery. This is accomplished using electrical circuit analogs such as the Randles circuit, which represents the electrode-electrolyte interface processes, and a minima search method. For model identification, a better fit of the impedance data was found using a two-electrode Randles circuit model (Figure 3).

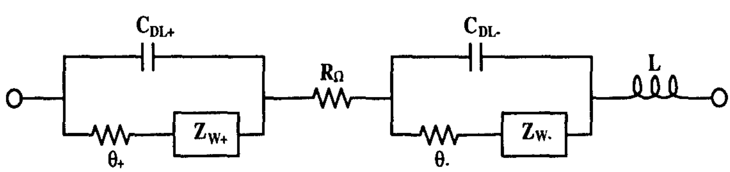

Figure 3. Two-electrode Randles circuit model with wiring inductance

The equation for this circuit is given as

$$Z_{cell}(s) = \frac{s^{1/2}\theta_+ + \sigma_+\sqrt{2}}{s^{1/2}\theta_+ C_{DL+} + sC_{DL+}\sigma_+\sqrt{2} + s^{1/2}} + R_\Omega + \frac{s^{1/2}\theta_- + \sigma_-\sqrt{2}}{s^{1/2}\theta_- C_{DL-} + sC_{DL-}\sigma_-\sqrt{2} + s^{1/2}} + sL \qquad (1)$$

In (1), $s = j\omega$ (ω is frequency in rad/s), R_Ω represents the electrolyte resistance, θ represents the charge transfer resistance, C_{DL} represents the double layer capacitance, σ represents the diffusion layer coefficient, and Z_{cell} represents the Warburg impedance (Z_W) of the cell. These parameters represent the physical electrochemical processes, such as charge and mass transfer, which occur during cycling. See [4], [5], [7] for a description of these electrochemical processes.

The above parameters are extracted from the impedance measurements using a minima search method. For this approach, a simulated annealing algorithm was chosen. Unlike many local minima search methods, simulated annealing offers a global search [8]-[11]. Search regions, based on the identified parameters from previous impedance measurements, are used to minimize processing iterations. The model-identified electrolyte resistance of a nickel-cadmium battery during discharge, which was found using simulated annealing as the minima search method, is shown in Figure 4.

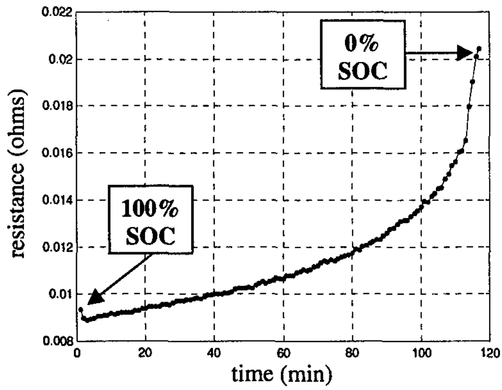

Figure 4. Model-identified electrolyte resistance of a nickel-cadmium battery using simulated annealing

State-of-Charge Prediction Models: The previous section addressed the extraction of physically meaningful parameters, such as charge transfer resistance, to more strongly connect SOC, SOH, and SOL predictions to internal battery processes. These *virtual sensor* signals (i.e., identified model parameters) also provide the decision processing with a check for bad signals. Referring to Figure 1, this section focuses on the developed SOC prediction modeling, primarily addressing the neural network and ARMA modeling and results. Work pertaining to the fuzzy logic prediction model is currently under investigation and results are being analyzed.

ARMA Modeling: Autoregressive (AR) modeling is a powerful linear modeling technique employed for predictive diagnostics [12], [3]. In order to assess battery capacity, an analytical model of battery dynamics is useful. Autoregressive moving average (ARMA) modeling is commonly used for system identification because it is linear and easy to implement. It is also a good complement to the more complex models (neural network and fuzzy logic) being used. An ARMA model was thus chosen for assessment of battery SOC and is represented by the equation:

$$y(t)=a\,X(t) + b\,X(t-1) + c_o\,y(t-1), \tag{2}$$

where y represents SOC, X represents a vector of model inputs, and a, b, and c_o represents the model coefficients. Model coefficients are calculated during training of the model, where a least squares fit of data from a previously discharged battery is

performed [13]. The model uses instantaneous measurements, as well as past measurements of the system, to monitor changes in the system. Inputs to the model include electrochemical impedance parameters, voltage, current and temperature measurements, and past SOC predictions.

The ARMA model has been trained and tested on five different kinds of batteries with varying size, chemistry, and type: two sizes of primary poly-carbonmonofluoride $(CF)_x$ lithium (C and 2/3 A), two sizes of secondary nickel-cadmium (C and D), and one size of secondary lead-acid (12 volt).

Initial testing was performed on eight size C and nine 2/3 A $(CF)_x$ lithium batteries. Training was performed on one battery of each size and used to predict the other batteries of the same size. As shown in Table I, the model was very effective for this battery chemistry. The average prediction error for both sizes was less than 3%.

Table I. Results of ARMA model SOC predictions

Chemistry	Size	# Cells	Type	Prediction Error (%)
Lithium[1]	C	1	Primary	2.18
Lithium[1]	2/3 A	1	Primary	2.87
NiCad[2]	D	1	Secondary	3.17
NiCad[2]	C	1	Secondary	4.50
Lead-Acid	12 Volt	6	Secondary	9.13

[1] Poly-carbonmonofluoride-lithium (spiral type)

[2] Nickel-cadmium

Tests were also performed on nine size C and nine size D nickel-cadmium batteries. Similar results were obtained for these batteries as well, with average prediction errors of less than 5% (Table I). Although these batteries are secondary cells, only a few cycles from each battery were completed for analysis.

Final testing was performed on five 12-volt lead-acid starter batteries containing six cells each. Because these batteries are secondary, training was performed on an initial cycle of each battery and retrained after every additional cycle. Despite the fact that health effects make prediction more difficult, the model performed well on this chemistry. As shown in Table I, average prediction error was less than 10%.

Neural Network Modeling: An *artificial neural network* is a parallel distributed processing system inspired by biological neural networks. It consists of information processing units, called *neurons* or units, that are interconnected through *connection weights* to produce a desired output in response to its inputs. For battery SOC predictions, networks were trained to produce either a direct prediction of SOC or an estimation of initial battery capacity during the first few minutes of the run. All networks used for battery SOC estimation contained one hidden layer of neurons. The backpropagation gradient decent learning algorithm was used, which utilizes the error signal to optimize the weights and biases of both network layers.

The performance of the neural networks for direct SOC prediction was found to be quite consistent. The results for size C lithium batteries (runs 9-16) and size 2/3 A lithium batteries (runs 17-25) are given in Table II.

Table II. Errors for neural network direct SOC prediction of $(CF)_x$ lithium batteries

Network Topology [# *Hidden Neurons*]	**Size**	**Average Training Error** [*Training Set*]	**Average Testing Error**	**Maximum Testing Error** [*Run #*]
Feed Forward [*6*]	C	0.2% [*14*]	2.5 %	6.0% [*11*]
Feed Forward [*6*]	2/3 A	1.5% [*18*]	5.0 %	7.4% [*17*]
Time Delay [*7*]	C	0.3% [*14*]	3.0 %	7.1% [*11*]
Time Delay [*7*]	2/3 A	0.8% [*18*]	4.7 %	8.0% [*20*]

Networks were also trained to estimate the initial capacity of the battery during the first few minutes of the test. The SOC of the battery was then calculated directly by using the cumulative discharge current. This method can be a powerful tool for *mission planning.* Hypothetical load profiles could be used to predict whether the battery would survive or fail during a given mission, thus preventing the high cost and risk of batteries failing in the field. Results of this network on lithium batteries are given in Table III.

Table III. Error rates for SOC prediction based on initial capacity estimation with neural networks for $(CF)_x$ lithium batteries

Network Topology [*#Hidden Neurons*]	**Size**	**Average Training Error** [*Training Set*]	**Average Testing Error**	**Maximum Testing Error** [*Run #*]
Feed-forward [*5*]	C	2.4 % [*13 14 16*]	5.7 %	9.1 % [*11*]
Feed-forward [*5*]	2/3 A	3.0 % [*17 18 20*]	7.9 %	10.4 % [*23*]
Radial Basis [*6*]	C	0.6% [*13 14 16*]	4.6 %	6.8 % [*15*]
Radial Basis [*11*]	2/3 A	2.3 % [*17 18 20*]	3.4 %	4.9 % [*19*]

The SOC assessment by neural networks was very good. Although the average error is slightly higher than for the ARMA predictors, two important strengths of the neural network predictors outweigh that drawback: (i) maximum error on outliers was not significantly larger than the average error, and (ii) the network provides a conservative prediction (i.e., it does not over-predict the SOC). Both of these advantages are very important in practical systems where certification and low false alarms can impact whether a system is actually used or shelved.

<u>SOC Modeling Remarks:</u> Considering that very little training data are used to produce the predictions, results for both types of models are quite impressive. As more data are collected and several runs of each level of initial battery SOC become available, the

robustness of the predictors is likely to improve. The key distinction between the ARMA and neural network approaches is that the ARMA model assumes an explicit linear form of the predictor, while the neural network attempts to discover an implicit nonlinear model that captures the intricacies of the battery dynamics. If the model is of adequate degree, the ARMA model should require fewer runs than the neural network. However, the neural network can better represent nonlinearity (i.e., a variable load) and, thus, provide better generalization across the sample.

The models performed poorly on two of the tested batteries, which are examples of *outliers* that can skew most predictors. For such cases, the best predictors do not attempt to accurately predict the outliers; instead they seek rough conservative estimates that will allow the system to quickly flag the outliers. In this case, the batteries likely were *faulty* in some respect. It is the focus of SOH research to identify and assess the severity of existing or impending battery faults and this topic is briefly discussed below. The benefit of a good initial capacity estimator is a valuable capability not only during the operational scenario, but also for quality control purposes.

Fault and End-of-Life Prediction: For primary batteries, the SOC is also the SOL; once the charge is depleted the battery cannot be used again. However for secondary batteries, the SOC only represents the cycle life and not the total life of the battery because multiple discharges are possible.

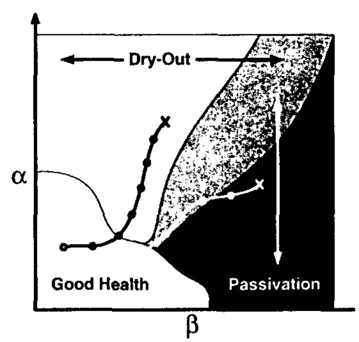

Figure 5. Failure identification using statistical pattern recognition

State-of-Health: For secondary batteries, the life of the battery is defined by the number of usable cycles that remain until failure. For example, batteries are commonly removed from service when their discharge capacity has been reduced to 65% of the original capacity, indicating the end limit for usable cycles [14]. Other end-of-life conditions include short-circuited cells and low terminal voltage. In addition, a number of ageing mechanisms (dry-out, passivation, etc.) progress during a battery's life, resulting in its eventual failure. Each mechanism wears the battery at a different rate and simultaneous failure progression is common. Identifying which faults are occurring and to what degree will dictate the SOL prediction model that should be used. This classification of faults is an estimation of the battery's SOH. Much like the SOC approach to having three separate, parallel processing methodologies for prediction, the SOH estimation processing involves three different processing branches: statistical pattern recognition using linear discriminant functions, neural network-based pattern recognition, and fuzzy logic-based classification [15], [16]. Figure 5 demonstrates an example of battery failure identification using statistical pattern recognition. Axis labels α and β represent measured or derived parameters that are used to identify the failures.

State-of-Life: Once faults and their severity are identified from the SOH processing, the proper SOL prediction model can be selected. Figure 6 shows a case where dry-out was identified as the dominant SOH condition in a lead-acid starter battery. As a result, a dry-out trained SOL predictor was used to predict the remaining usable cycles. Had a different dominant failure mechanism been identified from the SOH processing, a different SOL prediction model would have been used.

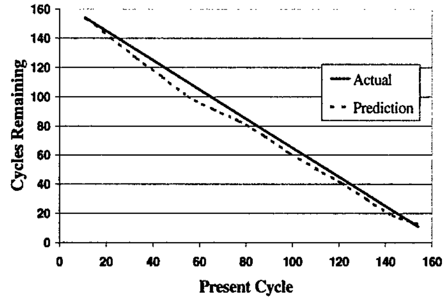

Figure 6. ARMA SOL prediction based on dry-out dominated SOH

Decision Fusion Processing: As previously mentioned, the SOC, SOH, and SOL processing makes three parallel predictions. This approach provides three assessments of the battery's condition. These three predictions are fed into a decision-processing module that determines the predictors' effectiveness relative to each other, processed sensor data, previous history, and knowledge about the battery type. The decision processing uses this information, via hybrid automated reasoning modules, to yield a combined prediction of the SOC, SOH, or SOL with a measure of confidence. Research on the decision-processing portion of the overall processing flow is currently under way. Referring to Figure 1, decision fusion represents the final stage of the processing; the output is then fed to a user interface that can display or coordinate the battery condition data.

Conclusions: Condition-based maintenance provides a means for improving the reliability of battery management in operational systems. For primary batteries, this represents using the full capacity of the battery before it is replaced. For secondary batteries, this represents cycling the battery to its true last usable cycle, rather then a conservative, statistical-based last cycle. In the case of a backup or standby battery, this represents knowledge of usage capacity prior to putting the battery online. The model-based approach described in this paper provides a framework for predicting SOC, SOH, and SOL. It has been shown that in addition to voltage, current and temperature, the internal electrical impedance of the battery ties closely to the physical processes that drive capacity and aging. A robust identification routine was developed and these identified parameters, along with measured signals, were used develop and test SOC, SOH, and SOL predictors. The developed ARMA and neural network SOC prediction models were discussed and shown to perform well across different battery chemistries and sizes. Some initial results were presented from the SOH and SOL prediction development; however, this work is still in its early stages. Finally, the framework for the decision fusion processing, which provides additional error checking and performance enhancement, was discussed. Most of the analyzed data was collected on a laboratory test stand under controlled conditions. Plans are being made to collect field data to test the developed model-based predictive diagnostics on battery systems (and other electrochemical energy sources) under real-world operating conditions.

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FAILURE MODES AND ANALYSIS II

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